What Boolean Algebras Can Teach Us About Weighted Model Counting

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1 Introduction

Contributions.

- WMC defines a measure over a BA.
- WMC with weights on literals imposes an independence assumption. (Measures are 'slightly' more expressive than WMC with weights on models because they apply to non-atomic BAs.)
- A BA can be augmented with new literals in order to support any measure.
- (Maybe) a lower bound on the number of new literals needed in order to support any measure.
- Alternatively, one can use coproducts and pushouts to define a BA with precisely the right independence and conditional independence conditions. (This requires a relaxed version of WMC.)
- This results in a smaller problem for WMC algorithms (w.r.t. both the number of literals and the length of the theory) and is optimal for, e.g., Bayesian networks.
- (Maybe) this results in faster inference (?)

Notable previous/related work.

- Hailperin's approach to probability logic [9]
- Nilsson's (somewhat successful) probabilistic logic [14]
- Logical induction: a big paper with a good overview of previous attempts to assign probabilities to logical sentences in a sensible way [7]
- Measures on Boolean algebras
 - On possibility and probability measures in finite Boolean algebras [2]
 - Representation of conditional probability measures [12]

2 Preliminaries

Definition 1. A Boolean algebra (BA) is a tuple $(\mathbf{B}, \wedge, \vee, \neg, 0, 1)$ consisting of a set **B** with binary operations meet \wedge and join \vee , unary operation \neg and elements $0, 1 \in \mathbf{B}$ such that the following axioms hold for all $a, b, \in \mathbf{B}$:

• both \wedge and \vee are associative and commutative;

- $a \lor (a \land b) = a$, and $a \land (a \lor b) = a$;
- 0 is the identity of \vee , and 1 is the identity of \wedge ;
- ∨ distributes over ∧ and vice versa;
- $a \vee \neg a = 1$, and $a \wedge \neg a = 0$.

For clarity and succinctness, we will occasionally use three other operations that can be defined using the original three¹:

$$a \to b = \neg a \lor b,$$

$$a \leftrightarrow b = (a \land b) \lor (\neg a \land \neg b),$$

$$a + b = (a \land \neg b) \lor (\neg a \land b).$$

We can also define a partial order \leq on \mathbf{B} as $a \leq b$ if $a = b \wedge a$ (or, equivalently, $a \vee b = b$) for all $a, b \in \mathbf{B}$. Furthermore, let a < b denote $a \leq b$ and $a \neq b$. For the rest of this paper, let \mathbf{B} refer to the BA $(\mathbf{B}, \wedge, \vee, \neg, 0, 1)$. For any $S \subseteq \mathbf{B}$, we write $\bigvee S$ for $\bigvee_{x \in S} x$ and call it the *supremum* of S. Similarly, $\bigwedge S = \bigwedge_{x \in S} x$ is the *infimum*. By convention, $\bigwedge \emptyset = 1$ and $\bigvee \emptyset = 0$. For any $a, b \in \mathbf{B}$, we say that a and b are *disjoint* if $a \wedge b = 0$.

Definition 2 ([10, 13]). An element $a \neq 0$ of **B** is an atom if, for all $x \in \mathbf{B}$, either $x \wedge a = a$ or $x \wedge a = 0$. Equivalently, $a \neq 0$ is an atom if there is no $x \in \mathbf{B}$ such that 0 < x < a. We say that **B** is atomic if for every $a \in \mathbf{B} \setminus \{0\}$, there is an atom x such that $x \leq a$.

Lemma 3 ([6]). For any two distinct atoms $a, b \in \mathbf{B}$, $a \wedge b = 0$.

Lemma 4 ([8]). The following are equivalent:

- B is atomic.
- For any $x \in \mathbf{B}$, $x = \bigvee_{atoms\ a \leq x} a$.
- 1 is the supremum of all atoms.

Lemma 5 ([8]). All finite BAs are atomic.

Definition 6 ([5, 10]). A measure on **B** is a function $m: \mathbf{B} \to \mathbb{R}_{\geq 0}$ such that:

- m(0) = 0;
- $m(a \lor b) = m(a) + m(b)$ for all $a, b \in \mathbf{B}$ whenever $a \land b = 0$.

If m(1) = 1, we call m a probability measure. Also, if m(x) > 0 for all $x \neq 0$, then m is strictly positive.

Definition 7 ([8]). Let **A** and **B** be BAs. A (Boolean) homomorphism from **A** to **B** is a map $f: \mathbf{A} \to \mathbf{B}$ such that:

- $f(x \wedge y) = f(x) \wedge f(y)$,
- $f(x \vee y) = f(x) \vee f(y)$,
- $f(\neg x) = \neg f(x)$

for all $x, y \in \mathbf{A}$.

Lemma 8 (Homomorphisms preserve order [8]). Let $f: \mathbf{A} \to \mathbf{B}$ be a homomorphism between two BAs \mathbf{A} and \mathbf{B} . Then, for any $x, y \in \mathbf{A}$, if $x \leq y$, then $f(x) \leq f(y)$.

¹We use + to denote symmetric difference because it is the additive operation of a Boolean ring.

Lemma 9 ([16]). For any $a, b \in \mathbf{B}$, $a \le b$ if and only if $a \land \neg b = 0$.

Lemma 10 ([8]). Let $m: \mathbf{B} \to \mathbb{R}_{>0}$ be a measure. Then for all $a, b \in \mathbf{B}$, if $a \leq b$, then $m(a) \leq m(b)$.

Definition 11 ([11]). Let S be a set, and let **B** be a BA. Then **B** is a *free BA over S* if there is a map $S \to \mathbf{B}$ such that for any BA **C** and map $S \to \mathbf{C}$, there is a unique homomorphism $\mathbf{B} \to \mathbf{C}$ that makes



commute. A BA ${f B}$ is ${\it free}$ if ${\it S}$ exists.

Lemma 12 ([16]). A finite BA is free if and only if it has 2^{2^n} elements for some $n \in \mathbb{N}$. It then has 2^n atoms and n generators.

3 WMC as a Measure

Definition 13. Let \mathcal{L} be a propositional (or first-order) logic, and let Δ be a theory in \mathcal{L} . We can define an equivalence relation on formulas in \mathcal{L} as

$$\alpha \sim \beta$$
 if and only if $\Delta \vdash \alpha \leftrightarrow \beta$

for all $\alpha, \beta \in \mathcal{L}$. Let $[\alpha]$ denote the equivalence class of $\alpha \in \mathcal{L}$ with respect to \sim . We can then let $B(\Delta) = \{ [\alpha] \mid \alpha \in \mathcal{L} \}$ and define the structure of a BA on $B(\Delta)$ as

$$\begin{split} [\alpha] \vee [\beta] &= [\alpha \vee \beta], \\ [\alpha] \wedge [\beta] &= [\alpha \wedge \beta], \\ \neg [\alpha] &= [\neg \alpha], \\ 1 &= [\alpha \to \alpha], \\ 0 &= [\alpha \wedge \neg \alpha] \end{split}$$

for all $\alpha, \beta \in \mathcal{L}$. Then $B(\Delta)$ is the *Lindenbaum-Tarski algebra* of Δ [11, 17].

Example 14. Let \mathcal{L} be a propositional logic with p and q as its only atoms. Then $L = \{p, q, \neg p, \neg q\}$ is its set of literals. Let $w : L \to \mathbb{R}_{>0}$ be the weight function defined by

$$w(p) = 0.3,$$

 $w(\neg p) = 0.7,$
 $w(q) = 0.2,$
 $w(\neg q) = 0.8.$

Let Δ be a theory in \mathcal{L} with a sole axiom p. Then Δ has two models, i.e., $\{p,q\}$ and $\{p,\neg q\}$. The weighted model count (WMC) [3] of Δ is then

$$\sum_{\omega \models \Delta} \prod_{\omega \models l} w(l) = w(p)w(q) + w(p)w(\neg q) = 0.3.$$

The corresponding BA $B(\Delta)$ can then be constructed using Definition 13. Alternatively, one can first construct the free BA generated by the set $\{p,q\}$ and then take a quotient with respect to either the filter generated by p or the ideal² generated by $\neg p$.

Each element of $B(\mathcal{L})$ can also be seen as a subset of the set of all models of \mathcal{L} , with 0 representing \emptyset , 1 representing the set of all (four) models, each atom representing a single model, and each edge going upward representing a subset relation. Thus, the Boolean-algebraic way of calculating the WMC of Δ consists of:

²More details on these concepts can be found in many books on BAs [8, 11].

- 1. Identifying an element $a \in B(\mathcal{L})$ that corresponds to Δ .
- 2. Finding all atoms of $B(\mathcal{L})$ that are 'dominated' by a according to the partial order.
- 3. Using w to calculate the weight of each such atom.
- 4. Adding the weights of these atoms.

This motivates the following definition of WMC generalised to BAs.

Definition 15. Let **B** be an atomic BA, and let $M \subset \mathbf{B}$ be its set of atoms. Let $L \subset \mathbf{B}$ be such that every atom $m \in M$ can be uniquely expressed as $m = \bigwedge L'$ for some $L' \subseteq L$, and let $w : L \to \mathbb{R}_{\geq 0}$ be arbitrary. The weighted model count $\mathrm{WMC}_w \colon \mathbf{B} \to \mathbb{R}_{\geq 0}$ is defined as

$$\operatorname{WMC}_{w}(x) = \begin{cases} 0 & \text{if } x = 0\\ \prod_{l \in L'} w(l) & \text{if } M \ni x = \bigwedge L'\\ \sum_{\operatorname{atoms } a \le x} \operatorname{WMC}_{w}(a) & \text{otherwise} \end{cases}$$

for any $x \in \mathbf{B}$. Furthermore, we define the normalised weighted model count $\mathrm{NWMC}_w \colon \mathbf{B} \to [0,1]$ as $\mathrm{NWMC}_w(x) = \frac{\mathrm{WMC}_w(x)}{\mathrm{WMC}_w(1)}$ for all $x \in \mathbf{B}$. For both WMC_w and NWMC_w , we will drop the subscript when doing so results in no potential confusion. Finally, we say that a measure $m \colon \mathbf{B} \to \mathbb{R}_{\geq 0}$ is a WMC measure (or is WMC-definable) if there exists a subset $L \subset \mathbf{B}$ and a weight function $w \colon L \to \mathbb{R}_{\geq 0}$ such that $m = \mathrm{WMC}_w$.

Theorem 16. WMC is a measure, and NWMC is a probability measure.

Proof. First, note that WMC is non-negative and WMC(0) = 0 by definition. Next, let $x, y \in \mathbf{B}$ be such that $x \wedge y = 0$. We want to show that

$$WMC(x \lor y) = WMC(x) + WMC(y). \tag{1}$$

If, say, x = 0, then Eq. (1) becomes

$$WMC(y) = WMC(0) + WMC(y) = WMC(y)$$

(and likewise for y=0). Thus we can assume that $x \neq 0 \neq y$ and use Lemma 4 to write

$$x = \bigvee_{i \in I} x_i$$
 and $y = \bigvee_{j \in J} y_j$

for some sequences of atoms $(x_i)_{i\in I}$ and $(y_j)_{j\in J}$. If $x_{i'}=y_{j'}$ for some $i'\in I$ and $j'\in J$, then

$$x \wedge y = \bigvee_{i \in I} \bigvee_{j \in J} x_i \wedge y_j = x_{i'} \wedge y_{j'} \neq 0,$$

contradicting the assumption. This is enough to show that

$$WMC(x \vee y) = WMC\left(\left(\bigvee_{i \in I} x_i\right) \vee \left(\bigvee_{j \in J} y_j\right)\right) = \sum_{i \in I} WMC(x_i) + \sum_{j \in J} WMC(y_j)$$
$$= WMC(x) + WMC(y),$$

finishing the proof that WMC is a measure. This immediately shows that NWMC is a probability measure since, by definition, NWMC(1) = 1.

Given a theory Δ in a logic \mathcal{L} , the usual way of using WMC to compute the probability of a query q is [1, 15]

$$\Pr_{\Delta, w}(q) = \frac{\mathrm{WMC}_w(\Delta \wedge q)}{\mathrm{WMC}_w(\Delta)}.$$

In our algebraic formulation, this can be computed in two different ways:

- as $\frac{\mathrm{WMC}_w(\Delta \wedge q)}{\mathrm{WMC}_w(\Delta)}$ in $B(\mathcal{L})$,
- and as $\text{NWMC}_w([q])$ in $B(\Delta)$.

But how does the measure defined on $B(\mathcal{L})$ transfer to $B(\Delta)$?

4 What Measures Are WMC-Definable?

4.1 WMC Requires Independent Literals

Lemma 17. For any measure $m: \mathbf{B} \to \mathbb{R}_{\geq 0}$ and elements $a, b \in \mathbf{B}$,

$$m(a \wedge b) = m(a)m(b) \tag{2}$$

if and only if

$$m(a \wedge b) \cdot m(\neg a \wedge \neg b) = m(a \wedge \neg b) \cdot m(\neg a \wedge b). \tag{3}$$

Proof. First, note that $a = (a \wedge b) \vee (a \wedge \neg b)$ and $(a \wedge b) \wedge (a \wedge \neg b) = 0$, so, by properties of a measure,

$$m(a) = m(a \wedge b) + m(a \wedge \neg b). \tag{4}$$

Applying Eq. (4) and the equivalent expression for m(b) allows us to rewrite Eq. (2) as

$$m(a \wedge b) = [m(a \wedge b) + m(a \wedge \neg b)][m(a \wedge b) + m(\neg a \wedge b)]$$

which is equivalent to

$$m(a \wedge b)[1 - m(a \wedge b) - m(a \wedge \neg b) - m(\neg a \wedge b)] = m(a \wedge \neg b)m(\neg a \wedge b). \tag{5}$$

Since $a \wedge b$, $a \wedge \neg b$, $\neg a \wedge b$, $\neg a \wedge \neg b$ are pairwise disjoint and their supremum is 1,

$$m(a \wedge b) + m(a \wedge \neg b) + m(\neg a \wedge b) + m(\neg a \wedge \neg b) = 1,$$

and this allows us to rewrite Eq. (5) into Eq. (3). As all transformations are invertible, the two expressions are equivalent. \Box

Theorem 18. Let **B** be a free BA over $\{l_i\}_{i=1}^n$ (for some $n \in \mathbb{N}$) with measure $m : \mathbf{B} \to \mathbb{R}_{\geq 0}$, and let $L = \{l_i\}_{i=1}^n \cup \{\neg l_i\}_{i=1}^n$. Then there exists a weight function $w : L \to \mathbb{R}_{\geq 0}$ such that $m = \mathrm{WMC}_w$ if and only if

$$m(l \wedge l') = m(l)m(l') \tag{6}$$

for all distinct $l, l' \in L$ such that $l \neq \neg l'$.

Remark. Note that if n = 1, then Eq. (6) is vacuously satisfied and so any valid measure can be expressed as WMC.

Proof. (\Leftarrow) Let $w: L \to \mathbb{R}_{\geq 0}$ be defined by

$$w(l) = m(l) \tag{7}$$

for all $l \in L$. We are going to show that $\mathrm{WMC}_w = m$. First, note that $\mathrm{WMC}_w(0) = 0 = m(0)$ by the definitions of both WMC_w and m. Second, let

$$a = \bigwedge_{i=1}^{n} a_i \tag{8}$$

be an atom in **B** such that $a_i \in \{l_i, \neg l_i\}$ for all $i \in [n]$. Then

WMC(a) =
$$\prod_{i=1}^{n} w(a_i) = \prod_{i=1}^{n} m(a_i) = m\left(\bigwedge_{i=1}^{n} a_i\right) = m(a)$$

by Definition 15 and Eqs. (6) to (8). Finally, note that if WMC and m agree on all atoms, then they must also agree on all other non-zero elements of the Boolean algebra.

(\Rightarrow) For the other direction, we are given a weight function $w: L \to \mathbb{R}_{\geq 0}$ that induces a measure $m = \text{WMC}_w: \mathbf{B} \to \mathbb{R}_{\geq 0}$, and we want to show that Eq. (6) is satisfied. Let $k_i, k_j \in L$ be such that $k_i \in \{l_i, \neg l_i\}, k_j \in \{l_j, \neg l_j\}$, and $i \neq j$ for some $i, j \in [n]$. We then want to show that

$$m(k_i \wedge k_j) = m(k_i)m(k_j) \tag{9}$$

which is equivalent to

$$m(k_i \wedge k_j) \cdot m(\neg k_i \wedge \neg k_j) = m(k_i \wedge \neg k_j) \cdot m(\neg k_i \wedge k_j)$$
(10)

by Lemma 17. Then

$$\begin{aligned} \operatorname{WMC}(k_i \wedge k_j) &= \sum_{\text{atoms } a \leq k_i \wedge k_j} \operatorname{WMC}(a) = \sum_{\text{atoms } a \leq k_i \wedge k_j} \prod_{m \in [n]} w(a_m) \\ &= \sum_{\text{atoms } a \leq k_i \wedge k_j} w(a_i) w(a_j) \prod_{m \in [n] \setminus \{i,j\}} w(a_m) = \sum_{\text{atoms } a \leq k_i \wedge k_j} w(k_i) w(k_j) \prod_{m \in [n] \setminus \{i,j\}} w(a_m) \\ &= w(k_i) w(k_j) \sum_{\text{atoms } a \leq k_i \wedge k_j} \prod_{m \in [n] \setminus \{i,j\}} w(a_m) = w(k_i) w(k_j) C, \end{aligned}$$

where C denotes the part of WMC $(k_i \wedge k_j)$ that will be the same for WMC $(\neg k_i \wedge k_j)$, WMC $(k_i \wedge \neg k_j)$, and WMC $(\neg k_i \wedge \neg k_j)$ as well. But then Eq. (10) becomes

$$w(k_i)w(k_j)w(\neg k_i)w(\neg k_j)C^2 = w(k_i)w(\neg k_j)w(\neg k_i)w(k_j)C^2$$

which is trivially true.

4.2 Extending the Algebra

Given this requirement for independence, a well-known way to represent probability distributions that do not consist entirely of independent variables is by adding more literals [3], i.e., extending the set L covered by the WMC weight function $w: L \to \mathbb{R}_{>0}$. Let us translate this idea to the language of BAs.

Theorem 19. Let **B** be a free BA over a finite set S, and let $m: \mathbf{B} \to \mathbb{R}_{\geq 0}$ be an arbitrary measure. Let $L = \{s \mid s \in S\} \cup \{\neg s \mid s \in S\}$. By Lemma 12, we know that **B** has $n = 2^{|S|}$ atoms. Let $\{a_i\}_{i=1}^n$ denote those atoms in some arbitrary order. Let $L' = L \cup \{\phi_i\}_{i=1}^n \cup \{\neg\phi_i\}_{i=1}^n$ be the set L extended with 2n new elements. Let \mathbf{B}' be the unique Boolean algebra with $\{\phi_i \land a_i\}_{i=1}^n \cup \{\neg\phi_i \land a_i\}_{i=1}^n$ as its set of atoms. Let $\iota: \mathbf{B} \hookrightarrow \mathbf{B}'$ be the inclusion homomorphism. Let $w: L' \to \mathbb{R}_{\geq 0}$ be defined by

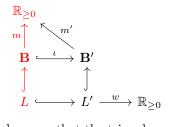
$$w(l) = \begin{cases} m(a_i)/2 & \text{if } l = \phi_i \text{ or } l = \neg \phi_i \text{ for some } i \in [n] \\ 1 & \text{otherwise} \end{cases}$$

for all $l \in L'$, and note that this defines a WMC measure $m' = WMC_w : \mathbf{B}' \to \mathbb{R}_{>0}$. Then

$$m(a) = (m' \circ \iota)(a)$$

for all $a \in \mathbf{B}$.

In other words, any measure can be computed using WMC by extending the BA with more literals. More precisely, we are given the left-hand column in



and construct the remaining part in such a way that the triangle commutes.

Proof. Since **B** is free over S, each atom $a_i \in \mathbf{B}$ is an infimum of elements in L, i.e.,

$$a_i = \bigwedge_{j \in J} a_{i,j}$$

for some $\{a_{i,j}\}_{j\in J}\subset L$. Moreover, each atom $b\in \mathbf{B}'$ can be represented as either $b=\phi_i\wedge a_i$ or $b=\neg\phi_i\wedge a_i$ for some atom $a_i\in \mathbf{B}$, also making it an infimum over a subset of L'. Then, for any $b\in \mathbf{B}$,

$$(m' \circ \iota)(b) = \sum_{\substack{\text{atoms } a_i \in \mathbf{B}: \\ \phi_i \wedge a_i < \iota(b)}} (w(\phi_i) + w(\neg \phi_i)) \prod_{j \in J} w(a_{i,j}),$$

recognising that, for any $\iota(b)$, any atom $a_i \in \mathbf{B}$ satisfies $\phi_i \wedge a_i \leq \iota(b)$ if and only if it satisfies $\neg \phi_i \wedge a_i \leq \iota(b)$. Then, according to the definition of w,

$$(m' \circ \iota)(b) = \sum_{\substack{\text{atoms } a_i \in \mathbf{B}: \\ \phi_i \wedge a_i < \iota(b)}} (w(\phi_i) + w(\neg \phi_i)) = \sum_{\substack{\text{atoms } a_i \in \mathbf{B}: \\ \phi_i \wedge a_i < \iota(b)}} m(a_i) = m(b),$$

provided that

$$\phi_i \wedge a_i \leq \iota(b)$$
 if and only if $a_i \leq b$,

but this is equivalent to

$$\phi_i \wedge a_i = \phi_i \wedge a_i \wedge b$$
 if and only if $a_i = a_i \wedge b$

which is true because $\phi_i \notin L$.

Now we can show that the construction in Theorem 19 is smallest possible.

Conjecture 20. Let \mathbf{B} and \mathbf{B}' be Boolean algebras, and $\iota \colon \mathbf{B} \hookrightarrow \mathbf{B}'$ be the inclusion map such that \mathbf{B} is free over L, all atoms of \mathbf{B}' can be expressed as meets of elements of L', and the following subset relations are satisfied:

$$\begin{array}{ccc} \mathbf{B} & \stackrel{\iota}{\longleftarrow} & \mathbf{B}' \\ \cup & & \cup \\ L & \subset & L' \end{array}$$

If, for any measure $m: \mathbf{B} \to \mathbb{R}_{\geq 0}$, one can construct a weight function $w: L' \to \mathbb{R}_{\geq 0}$ such that the WMC measure WMC: $\mathbf{B}' \to \mathbb{R}_{\geq 0}$ with respect to w satisfies

$$m = \text{WMC} \circ \iota$$

then $|L' \setminus L| \geq 2^{|L|+1}$.

Let us note how our lower bound on the number of added literals compares to two methods of translating a discrete probability distribution into a WMC problem over a propositional knowledge base proposed by Darwiche [4] and Sang et al. [15]. Suppose we have a discrete probability distribution with n variables, and the ith variable has v_i values, for each $i \in [n]$. Interpreted as a logical system, it has $\prod_{i=1}^{n} v_i$ models. My expansion would then use

$$\sum_{i=1}^{n} v_i + 2 \prod_{i=1}^{n} v_i$$

variables, i.e., a variable for each possible variable-value assignment, and two additional variables for each model. Without making any independence assumptions, the encoding by Darwiche [4] would use

$$\sum_{i=1}^{n} v_i + \sum_{i=1}^{n} \prod_{j=1}^{i} v_j$$

variables, while for the encoding by Sang et al. [15],

$$\sum_{i=1}^{n} v_i + \sum_{i=1}^{n} (v_i - 1) \prod_{j=1}^{i-1} v_j$$

variables would suffice.

5 Representing Independence and Conditional Independence

5.1 Preliminaries

Definition 21. Given a BA **A**, a *subalgebra* is a subset $\mathbf{B} \subseteq \mathbf{A}$ that, together with the operations, zero, and one of **A**, is a BA.

Definition 22 ([8]). Let **A**, **B**, and **C** be BAs such that **B** is a subalgebra of **A**. Let $f: \mathbf{A} \to \mathbf{C}$ and $g: \mathbf{B} \to \mathbf{C}$ be homomorphisms. Then f is an extension of g if f(x) = g(x) for all $x \in \mathbf{B}$. If f is an extension of each member of a family $\{g_i\}_{i \in I}$ of homomorphisms, then f is called a *common extension* of $\{g_i\}_{i \in I}$.

Definition 23 ([8]). Let $\{\mathbf{A}_i\}_{i\in I}$ be a family of subalgebras of a BA \mathbf{A} . If for any BA \mathbf{B} with a family of homomorphisms $\{f_i \colon \mathbf{A}_i \to \mathbf{B}\}_{i\in I}$ there exists a unique common extension of $\{f_i \colon \mathbf{A}_i \to \mathbf{B}\}_{i\in I}$ ($f \colon \mathbf{A} \to \mathbf{B}$ in the diagram),

$$\begin{array}{c}
\mathbf{A}_i & \longrightarrow \mathbf{A} \\
\downarrow_f \\
\downarrow_B
\end{array}$$

then **A** is the *internal sum*³ of $\{\mathbf{A}_i\}_{i\in I}$. We will denote it as $\bigoplus_{i\in I} \mathbf{A}_i$.

Proposition 24 ([16]). Let **A** be the internal sum of a family of BAs $\{\mathbf{A}_i\}_{i\in I}$, and let $\{m_i : \mathbf{A}_i \to \mathbb{R}_{\geq 0}\}_{i\in I}$ be a family of measures. Then there exists a unique measure $m : \mathbf{A} \to \mathbb{R}_{\geq 0}$ such that, for any finite subset $J \subseteq I$ and family of elements $\{x_j \in \mathbf{A}_j\}_{j\in J}$,

$$m\left(\bigwedge_{j\in J} x_j\right) = \prod_{j\in J} m_j(x_j).$$

³A slightly more general version of this definition is also known as the free product, the Boolean product, and the coproduct in the category of BAs [8, 11, 16].

Definition 25 ([11]). Let **A** be a BA. Let **B** be a subalgebra of **A**, and let $\{\mathbf{A}_i\}_{i\in I}$ be a family of subalgebras of **A** such that $\mathbf{A}_i \cap \mathbf{A}_j = \mathbf{B}$ for all $i \neq j$ in I. Let $\{\iota_i \colon \mathbf{B} \to \mathbf{A}_i\}$ be a family of inclusion homomorphisms. Then **A** is the *amalgamated free product*⁴ of $\{\mathbf{A}_i\}_{i\in I}$ over **B** if, for any Boolean algebra **C** with a family of homomorphisms $\{f_i \colon \mathbf{A}_i \to \mathbf{C}\}_{i\in I}$ such that $f_i \circ \iota_i = f_j \circ \iota_j$ for all $i, j \in I$, there is a unique homomorphism $f \colon \mathbf{A} \to \mathbf{C}$ such that the triangle in

$$\mathbf{B} \xrightarrow{\iota_i} \mathbf{A}_i \longleftrightarrow \mathbf{A}$$

$$f_i \downarrow \qquad f$$

$$\mathbf{C}$$

commutes for all $i \in I$. We will denote this product as

$$\mathbf{A} = igoplus_{i \in I} \mathbf{A}_i.$$

5.2 New Results

Theorem 26. Let $\{S_i\}_{i=0}^n$ be a finite set of finite sets for some n > 1 such that for all distinct positive integers i and j, $S_i \cap S_j = S_0$, and let

$$\mathbf{A} = \bigoplus_{\substack{\mathcal{F}(S_0)\\1 \le i \le n}} \mathcal{F}(S_i).$$

Let $(m_i: \mathcal{F}(S_i) \to \mathbb{R}_{\geq 0})_{i=1}^n$ be arbitrary measures. Then there is a unique measure $m: \mathbf{A} \to \mathbb{R}_{\geq 0}$ such that, for any element $b \in \mathcal{F}(S_0)$, subset $J \subseteq \{1, 2, \ldots, n\}$, and elements $\{a_j \in \mathcal{F}(S_j \setminus S_0)\}_{j \in J}$,

$$m\left(b \wedge \bigwedge_{j \in J} a_j\right) = \prod_{j \in J} m_j (b \wedge a_j).$$

Proof.

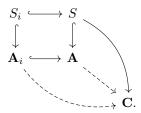
Theorem 27. The number of weights needed to encode a Bayesian network using coproducts and pushouts is equal to the number of entries in the tables of the network (and the resulting theory is shorter).

Theorem 28 (Pushouts of free BAs are free). Let

$$\mathbf{A} = \bigoplus_{\substack{\mathbf{B} \ i \in I}} \mathbf{A}_i$$

be an amalgamated free product such that $\{A_i\}_{i\in I}$ are free BAs with $\{S_i\}_{i\in I}$ as their respective sets of generators. Let $S = \bigcup_{i\in I} S_i$. Then **A** is a free BA with generating set S.

Proof. Suppose we have a map from S to an arbitrary BA \mathbb{C} , as in



We want to show that there exists a unique homomorphism $\mathbf{A} \to \mathbf{C}$. For all $i \in I$, from $S_i \hookrightarrow S$ and $S \to \mathbf{C}$ we get a map $S_i \to \mathbf{C}$, so—by the definition of a free BA—there is a unique homomorphism $\mathbf{A}_i \to \mathbf{C}$. Furthermore, a family of homomorphisms $\{\mathbf{A}_i \to \mathbf{C}\}_{i \in I}$ uniquely determine a homomorphism $\mathbf{A} \to \mathbf{C}$ by the universal mapping property of a (wide) pushout. Thus \mathbf{A} is a free BA with generating set S.

⁴Also known as a (wide) pushout in the category of BAs.

6 How to represent a Bayesian network

Let G = (V, E) be a DAG, and let $(X_v)_{v \in V}$ be the discrete random variables (RVs). Let $(d_v)_{v \in V}$ denote the numbers of values that each RV can take and assume that d_v is a power of two for all $v \in V$.

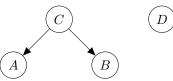
- 1. For each $v \in V$, let A_v be a set of $\log_2 d_v$ Boolean variables. (If d_v is not a power of two, we would need to manually forbid each illegal value, e.g., by adding formulas such as $\neg(x_1 \land x_2 \land x_3 \land \neg x_4)$ to the theory. Alternatively, we could set their probability to zero, but the former should be better.)
- 2. For $v \in V$:
 - (a) If v has no parents, we can directly provide a probability measure on $\mathcal{F}(A_v)$.
 - (b) Otherwise, we need a probability measure on

$$\mathcal{F}\left(A_v \cup \bigcup_{(u,v) \in E} A_u\right).$$

For any element $a_u \wedge a_v$ in this free Boolean algebra such that $a_v \in A_v \setminus \{0,1\}$, and $a_u \notin A_v$, we can set

$$m(a_u \wedge a_v) = \Pr(a_v \mid a_u) \Pr(a_u).$$

3. When a #SAT algorithm asks for the weight of a model $\bigwedge_{v \in V} l_v$, split it into segments that correspond to each leaf, take the probabilities from each such node, and multiply them. NB: The segments will intersect, e.g., with



 $a \wedge b \wedge c \wedge d$ will be split into $(a \wedge c) \wedge (b \wedge c) \wedge d$.

6.1 Bayesian networks as Boolean algebras

To turn a Bayesian network into a Boolean algebra, run $f(\{v \in V \mid \text{outdeg}(v) = 0\})$, where f works as follows on an arbitrary $A \subseteq V$:

- 1. $S \leftarrow \{u \mid (u, v) \in E, v \in A\}$ (i.e., S is the set of parents of the elements in A).
- 2. If $S = \emptyset$, return $\sum A$ (a coproduct).
- 3. Otherwise, return $\sum_{f(S)} A$ (a pushout).

Notes on the implementation of the algorithm

- We extend the Gaifman graph to add edges when two variables occur in the same CPT (e.g., including the edge from A to B when the CPT is $Pr(A \mid B)$).
- Extra benefit: one does not need to come up with a way to turn some probability distribution to into a fully independent one.
- Trivial CPTs such as $Pr(A \mid B) = Pr(\neg A \mid B) = 0.5$, the ADDs of which simplify to a single number, are put in the first cluster.

Table 1: Examples of how Bayesian networks encode as Boolean algebras. Here, A denotes $\mathcal{F}\{a\}$ and AB denotes $\mathcal{F}\{a,b\}$.

| Bayesian network | | Boolean algebra | |
|---|--------------|---|-------------------------|
| $\overline{\hspace{1cm}}$ | | | A |
| $\overline{\hspace{1cm}}$ | $\bigcirc B$ | | A + B |
| A B | | AB | |
| $\begin{array}{c c} \hline & A \\ \hline & & \\ \hline & B \\ \hline \end{array}$ | <u>C</u> | | $B +_A C$ |
| $\begin{array}{c} \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\$ | C D | | $B +_{A+C} D$ |
| A | C | $ \begin{array}{c} D \\ \downarrow \\ E \end{array} $ | $B +_{A+D} C +_{A+D} E$ |

- TODO: Look into ways to theoretically justify the performance benefits (I have some suggestions in my notes).
- TODO: when performing experiments, measure memory usage as well.
- TODO: Along with comparing the (3?) encodings, I could also compare this to using ADDs directly on Bayesian networks.
- TODO: Feedback: Give a concrete example of something impossible to represent using WMC.

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